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Displacement and spillover effects of soybean and sugarcane on Amazon deforestation: A spatial analysis of indirect land-use change in Brazil

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ABSTRACT

Global demand for food and biofuels has accelerated the expansion of agricultural frontiers, intensifying deforestation in tropical regions such as the Brazilian Amazon. While cattle ranching remains the primary direct driver, a substantial share of forest loss stems from indirect land-use change (ILUC) associated with soybean and sugarcane expansion in distant regions. Using a spatial dynamic panel model and economic, political, and land-use data, this study quantifies the magnitude and spatial diffusion of these indirect effects. Results indicate that soybean expansion indirectly accounted for 21,400 km² of deforestation (13.7% of the total), whereas sugarcane expansion contributed 42,300 km² (26.7%). These findings reveal strong cross-regional displacement dynamics within Brazil's land-use system, showing that deforestation in the Amazon is partly driven by agricultural expansion outside the biome. Policies focused solely on local control are therefore insufficient; spatially coordinated strategies are required to internalize ILUC effects and foster sustainable land-use transitions.

PALAVRAS-CHAVE

Indirect Land Use Changes, Displacement, Spillovers, Deforestation, Amazon

Efeitos de deslocamento e *spillover* da soja e da cana-de-açúcar sobre o desmatamento da amazônia: Uma análise espacial da mudança indireta no uso da terra no Brasil

RESUMO

A demanda global por alimentos e biocombustíveis tem acelerado a expansão das fronteiras agrícolas, intensificando o desmatamento em regiões tropicais como a Amazônia brasileira. Embora a pecuária permaneça como o principal determinante direto, uma parcela substancial da perda florestal decorre de mudanças indiretas no uso da terra (ILUC) associadas à expansão da soja e da cana-de-açúcar em regiões não amazônicas. Utilizando um modelo espacial dinâmico de painel e dados econômicos, políticos e de uso da terra, este estudo quantifica a magnitude e a difusão espacial desses efeitos indiretos. Os resultados indicam que, ao longo do período 2002–2011, a expansão da soja foi indiretamente responsável por 21.400 km² de desmatamento (13,7% do total), enquanto a expansão da cana-de-açúcar contribuiu com 42.300 km² (26,7%). Esses achados revelam fortes dinâmicas de deslocamento inter-regional no uso e na cobertura da terra no Brasil, demonstrando que o desmatamento na Amazônia é parcialmente impulsionado pela expansão agrícola fora desse bioma. Assim, políticas focadas exclusivamente no controle local são insuficientes; estratégias espacialmente coordenadas são necessárias para internalizar os efeitos de ILUC e promover transições sustentáveis na produção agropecuária nacional.

KEYWORDS

Mudanças indiretas no uso da terra, deslocamento, efeitos de transbordamento, desmatamento, Amazônia

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1. Introduction

Global demand for food and biofuels has sharply increased, driven by population growth and rising per capita income. This demand has led to significant land use and cover changes, especially in agricultural frontiers Barona et al. (2010); Arima et al. (2011); Das e Gundimeda (2022); Damm et al. (2024). The Brazilian Amazon, as the world's most active agricultural frontier, has experienced substantial forest loss and CO2 emissions, which raise serious environmental concerns Assunção et al. (2015).

While cattle ranching remains the primary direct driver of deforestation in the Amazon due to herd expansion McManus et al. (2016); Freitas Júnior e Barros (2021), a large portion of forest clearings is indirectly caused by Indirect Land Use Changes (ILUC). These changes are driven by the expansion of agricultural activities like soybean and sugarcane, which adopt advanced technologies and offer higher returns. ILUC occurs when these high-value crops encroach on pasturelands, pushing cattle ranching into new frontier regions. This displacement, coupled with inelastic demand for agricultural products, increases pressure on forested areas, causing deforestation Barona et al. (2010); Lapola et al. (2010); Arima et al. (2011); Andrade de Sá et al. (2013); Gollnow e Lakes (2014); Richards et al. (2014); Jusys (2016); SantAnna (2024); Guye (2025).

During the 2000s, the Brazilian Amazon deforestation peaked in 2004, with approximately 28,000 km² of forest clearings Hargrave e Kis-Katos (2013); Assunção et al. (2015). In response, the government and the soybean and cattle industries developed policies to control deforestation. Key initiatives included the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm)[1], the expansion of protected areas and indigenous lands, the List of Priority Municipalities, environmental compliance for rural credit, and the Soybean and Cattle Moratorium. Despite some leakages and spillovers shifting forest clearing to other regions Amin et al. (2019); Assunção et al. (2019); Moffette e Gibbs (2021), these policies reduced deforestation by 80% by 2012, bringing it down to 4,500 km².

Despite the reduction in forest clearings in this period, the expansion of soybean and sugarcane in Brazil continued to have indirect effects on the Amazon Barona et al. (2010); Lapola et al. (2010); Arima et al. (2011); Andrade de Sá et al. (2013); Gollnow e Lakes (2014); Richards et al. (2014); Jusys (2016); SantAnna (2024). However, measuring these indirect effects is challenging due to significant spatial and dynamic interactions, and no papers in the literature have incorporated both types of interactions within the same empirical design. Additionally, the existing literature does not explicitly account for conservation policy changes and their potential spillover effects, which could influence both forest clearings and indirect effects, introducing bias into the results.

[1]This plan integrated actions for territorial administration and environmental monitoring and control.

In summary, it is crucial to investigate and identify possible complex spatial patterns of land use change, as deforestation in frontier regions may be interconnected with agricultural expansion in other, even distant, locations. Additionally, the magnitude of these indirect effects can change over time, depending on market conditions and conservation policies, particularly in the presence of leakages and spatial spillovers.

This paper uses economic, political, and land use changes from 2002 to 2011 to measure the indirect effects of soybean and sugarcane expansion on the Brazilian Amazon deforestation while controlling for invariant factors such as climate, geographic location, and structural characteristics. Specifically, we investigate the relationship between deforestation in a given location and the expansion of soybean and sugarcane in nearby and distant regions. To achieve this, we use spatial econometric models, starting with a general approach using the Dynamic Spatial Durbin Model (DSDM) as proposed by Elhorst (2014), to account for both spatial and dynamic interactions.

Finally, to detail the goals, methodologies, and results, the article is structured into four sections, including this introduction. The second section presents the theoretical framework for Indirect Land Use Change (ILUC), the institutional context, and spatial interactions and spillovers. The third section details the empirical design and database. The remaining sections present the results and the final considerations.

2. Theoretical Framework

2.1 Indirect Land Use Change (ILUC)

The agricultural sector plays a key role in economic development by driving structural changes and income growth. The expansion of soy and sugarcane in Brazil during the 2000s, for example, positively impacted social and economic conditions Richards et al. (2014); Bustos et al. (2016). Brazilian agribusiness has generally intensified its production through technology adoption and large-scale mechanization, making the country more competitive in the international market and one of the largest exporters of agricultural goods in the world Barona et al. (2010).

However, the indirect land use changes caused by soybean and sugarcane, two major agricultural activities in Brazil, reduce the economic, social, and environmental benefits of these crops by displacing cattle to agricultural frontier regions, leading to deforestation Barona et al. (2010); Lapola et al. (2010); Arima et al. (2011); Andrade de Sá et al. (2013); Gollnow e Lakes (2014); Richards et al. (2014); Jusys (2016); SantAnna (2024). For instance, soybean expansion was responsible, directly or indirectly, for approximately 33% of deforestation in the Brazilian Amazon Richards et al. (2014), and sugarcane for 10% Jusys (2016).

Land use changes are driven by structural variables (market access and institutions), human decisions (migration), and geographic characteristics (soil quality and climatic conditions). In this context, ILUC is defined as changes in one location induced by changes in other regions. Three underlying mechanisms deserve attention: (i) demand, which changes the relative prices of agricultural activities and increases the return on beef; (ii) supply, which releases physical, human, and financial capital, directing resources to agricultural frontier regions where the opportunity cost is lower; and (iii) land price increases due to greater competition for its use (Andrade de Sá et al., 2013; Richards et al., 2014).

Agricultural supply and demand shocks—such as those triggered by biofuel mandates—can indirectly drive land expansion across crops and regions. These findings show that indirect land use change mechanisms operate through interconnected commodity markets, emphasizing the need to consider such spillover effects when evaluating agricultural and environmental policies (Guye (2025)). Empirical evidence from Brazil shows that most of the expansion in sugarcane ethanol production has occurred through increases in cultivated area rather than productivity gains, with a non-negligible share linked to direct deforestation. These findings underscore that, while biofuels can contribute to reducing carbon emissions, their large-scale expansion may generate unintended land-use and environmental consequences (SantAnna, 2024).

To make matters worse, the average productivity of displaced agricultural activities is lower in frontier regions, requiring more land to maintain constant production levels (Lapola et al., 2010). In this context, the beneficial effects of conservation policies and biofuels may be minimized or even neutralized due to the presence of ILUC (Barona et al., 2010; Jusys, 2016; SantAnna, 2024).

2.2 Institutional Context

The decision to deforest is largely influenced by various economic, social, and political forces that affect the cost-benefit analysis of forest clearing. For example, higher agricultural commodity prices, market access, and inadequate conservation policies create incentives for deforestation (Barbier e Burgess, 2001). Therefore, institutional changes, especially in governance, are crucial for forest resource preservation, particularly because most forest areas in developing countries are under public or weak property rights (Bhattarai e Hammig, 2004).

Large-scale deforestation in the Brazilian Amazon began after the 1960s with infrastructure and colonization projects aimed at developing and occupying the region. Notable initiatives included the construction of highways connecting the Amazon to the rest of the country, subsidized credit, and colonization incentives. Since the 1980s, deforestation has been increasingly driven by commodity market dynamics, particularly for cattle ranching and soybeans (Barbier e Burgess, 2001; Hargrave e Kis-Katos, 2013; Assunção et al., 2015; Damm et al., 2024).

During the 2000s, the Brazilian government enhanced its Amazon conservation policy by increasing law enforcement, expanding protected areas, and restricting rural credit access. In 2004, the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAM) was launched to coordinate conservation efforts among various stakeholders. A key measure of PPCDAM was the creation of DETER (Real Time Deforestation Detection System), which uses satellite images to monitor deforestation every 15 days. DETER aims to identify deforestation hot spots in near real-time and alert authorities, particularly IBAMA, for immediate action. This system significantly improved deforestation control in Brazil, especially in high-risk areas, by replacing the less effective voluntary reporting system.

From the mid-2000s onwards, protected areas and indigenous territories in the Legal Amazon expanded rapidly, resulting in approximately 43% of the region being under protection by the end of the decade. These protected areas generally inhibit the advance of deforestation, especially in regions with significant human pressures, by making it more difficult to obtain legal land titles and increasing the likelihood of punishment for illegal deforestation. However, the literature indicates possible spillover effects, which shift forest clearing to other regions, thereby reducing the net benefits of these protective measures Cisneros et al. (2015); Amin et al. (2019).

Finally, in 2008, the Brazilian government created the List of Priority Municipalities to increase the focus of environmental conservation policies in the Amazon. In addition, Presidential Decree 6,514 of July 2008 provided legal support for more effective law enforcement. This decree increased the instruments for curbing environmental crimes, such as the increase in the amount and value of fines, as well as the seizure and destruction of assets used by offenders. In the same year, the National Monetary Council, through Resolution 3,545, turned the granting of rural credit in the Amazon biome conditional on compliance with environmental laws and ownership of a property title. Considering that most rural producers in the region either did not fully comply with environmental legislation or did not have definitive property titles, the resolution caused a significant drop in credit granted, especially among ranchers Assunção et al. (2019). Overall, these conservation policies contributed to a significant reduction in deforestation, declining forest clearings by nearly 80% between 2004 and 2012, falling from about 28,000 km² to 4,500 km² PRODES/INPE (2025).

2.3 Spatial Interactions and Spillovers

Spatial interactions and spillovers, which transmit impacts to neighboring regions, can amplify or neutralize the benefits of conservation programs and should therefore be considered to avoid biased results Cisneros et al. (2015); Pfaff e Robalino (2017); Amin et al. (2019); Assunção et al. (2019). According to Pfaff e Robalino (2017), spillovers influence the effectiveness of conservation programs through five channels:

1. Input Reallocation: Restrictions on certain properties can lead economic agents

to shift land use to areas with fewer restrictions, freeing up resources that may induce deforestation elsewhere.

2. Market Prices: Conservation policies can alter supply, demand, and market prices, encouraging production in untreated areas and potentially causing deforestation.

3. Learning: Policies can promote technology adoption and diffusion, increasing productivity and profitability, which can amplify local impacts and spillovers.

4. Nonpecuniary Motivations: Agents' behavior can be influenced by social and cultural norms and perceptions of justice, affecting conservation outcomes.

5. Ecological-Physical Links: Ecological and physical processes can create significant spillovers that impact conservation policy effectiveness.

Finally, it is worth noting that agricultural frontier expansion is a dynamic process that creates new agglomerations, propagating to neighboring regions through significant externalities Igliori (2006).

3. Empirical Design

3.1 Database

Land use change is a dynamic process with significant temporal and spatial relationships due to indirect effects, which must be considered in empirical estimates. Cross-sectional data cannot effectively identify these impacts, whereas panel data are more suitable as they allow control of fixed characteristics and temporal trends. This paper uses panel data from municipalities in the Legal Amazon from 2003 to 2011, integrating information from Cisneros et al. (2015); Koch et al. (2019); Assunção et al. (2019) with data collected and processed by the authors. The period was selected because it represents a phase of declining deforestation combined with major institutional advances and the rapid expansion of soybean and sugarcane production driven by the international commodity boom.

Data on deforestation in the Legal Amazon are sourced from the Brazilian government's PRODES/INPE, using Landsat-type satellite images aggregated at the municipal level. Deforestation data for year t cover forest suppressions from August 1st of year $t-1$ to July 31st of year t. Consequently, cattle and soy prices and conservation policy variables were constructed based on the same period. Furthermore, we normalized the annual increments of forest clearing to reduce excessive variations due to municipal area heterogeneities. The sample includes municipalities with more than 10% remaining forest at the beginning of the period to achieve a better model fit. This restriction helps avoid structural zeros and improves the stability of the spatial estimations, since deforestation dynamics can only be meaningfully analyzed in locations where forest is still available to be cleared. As municipalities with almost no remaining forest areas cannot present forest clearings, their inclusion would bias our main estimates. After applying this threshold, the sample was reduced from 760 to 490 municipalities, ensuring consistent spatial dependence and model performance. Although PRODES uses dry-season satellite images, measurement errors may still occur due to clouds, smoke, and shadows. To minimize these errors and avoid bias, all estimates include the proportion of clouds and unobserved areas.

The expansion of soy and cattle raising in the Amazon was considered in two ways: (i) with a time lag, $t-1$; and (ii) as the first difference, measuring the increase in planted area and the number of heads between $t-1$ and t. This approach aims to measure the impacts of Amazon deforestation without introducing endogeneity. The expansion of soy and sugarcane in other Brazilian municipalities was calculated based on variations between $t-2$ and $t-1$, representing the indirect effects of this expansion on cattle ranching displacement to the Amazon. The data for these variables are from the Municipal Agricultural Research (PAM) and the Municipal Livestock Research (PPM) conducted by the Brazilian Institute of Statistics and Geography (IBGE).

Considering that local commodity prices are endogenous to agricultural production and economic activity in the region, exogenous variations are necessary. Therefore, we used variations in soybean and livestock prices from Paraná, a non-Amazonian state, to construct the variables, as suggested by Assunção et al. (2019). We then built an indicator that captures the impact of exogenous price variations while accounting for the importance of the activity in each municipality, represented by the proportion of the municipal area dedicated to that crop. Algebraically,

$$PPA_{itc} = PP_{tc} * A_{ic,2000-2001} \tag{1}$$

where PPA_{itc} is the real weighted price of agricultural activity c in municipality i and year t; PP_{tc} is the price c in year t; $A_{ic,2000-2001}$ is the proportion of area in municipality i destined to activity c in the year 2000-2001. This indicator represents the importance of the agricultural activity for the municipality, assuming that greater dependence on the activity results in a greater impact from price changes.

Our empirical strategy also controls for changes in institutional characteristics, particularly those related to conservation policies. By prohibiting or altering incentives, these policies can directly and indirectly affect deforestation rates by influencing economic agents' decisions on land use. During the period considered, the Brazilian government made significant changes to its environmental policy for the Amazon, which were controlled using: (i) the value of environmental fines; (ii) the proportion of embargoed areas to capture environmental law enforcement; (iii) protected areas; (iv) amount of rural credit to capture access restrictions; (v) a dummy for priority municipalities defined after their inclusion in the list; (vi) area of the municipality covered by the Rural Environmental Registry (CAR); and (vii) party diversity of political representatives to represent institutional quality. Finally, although physical, geographic, and infrastructure characteristics such as soil quality, elevation, altitude, and distance to markets affect deforestation and agricultural production, they are relatively fixed over time and can be controlled through fixed effects. Correlations statistics between the variables are found in Appendices A.

3.2 Empirical Strategy

This paper uses economic, institutional, and land use changes in the Legal Amazon to capture the indirect effects of soybean and sugarcane expansion in Brazil, while controlling for invariant factors. Specifically, we estimated a fixed-effect panel data regression to capture unobserved heterogeneities, as this approach controls for fixed differences in historical, structural, geographic, climatic, cultural, political, economic, and social factors, as well as macroeconomic and technological shocks. This method also partially controls for characteristics that change slowly over time, such as proximity to cities, rivers, highways, other market accesses, and fragmented forests.

However, an important assumption of the model is that cross-sectional units are independent, which is generally not the case with spatial data due to spatial interactions and spillovers Pfaff e Robalino (2017). Spatial spillovers can affect the relationship between land use change and forest clearings, as deforestation can spread to neighboring regions. Considering spatial autocorrelation is crucial for two reasons: (i) effective local conservation policies can influence deforestation in neighboring areas; (ii) omitted variables can be spatially correlated, reducing omitted-variable bias. Therefore, in addition to the fixed-effect panel data model, we also estimated several spatial models to capture these effects.

Spatial relationships are modeled in spatial econometrics using spatial weight matrices based on criteria such as contiguity, inverse distance, and k-nearest neighbors. The spatial matrix W reflects hypotheses about spatial interactions between units, with zeros on the diagonal (indicating no self-neighbors) and the remaining cells capturing these interactions. Normalizing the matrix is crucial to avoid non-explosive processes and keep the estimated spatial coefficient between zero and one. In this paper, we follow Elhorst (2014) by initially estimating a Dynamic Spatial Durbin Model (DSDM) and then testing it against simpler spatial models. This approach considers the dynamic and spatial aspects of deforestation to measure the indirect effects of land use change in Brazil, generically represented as:

$$
\begin{aligned}
Deforest_{i,t} = \alpha Deforest_{i,t-1} + \rho W_1 Deforest_{J,t} \\
&+ \beta_1 Cattle_{i,t-1} + \beta_2 Soy_{i,t-1} \\
&+ \beta_3 \left(Cattle_{i,t-1} \times SoyBr_{t-2}\right) + \\
&\beta_4 \left(Cattle_{i,t-1} \times SugarcaneBr_{t-2}\right) \\
&+ \beta_5 Prices_{i,t-1} \\
&+ \beta_6 Policies_{i,t} + \beta_7 W_1 X_{j,t} + u_i + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

where $Deforest_{i,t}$ is the normalized deforestation rate in municipality i in year t; W_1 is the spatial weight matrix representing neighborhood relationships between municipalities; $D_{i,t-1}$ and $W_1 D_{j,t}$ are the temporal and spatial lags, respectively; u_i controls for municipality fixed effects; $Cattle_{i,t-1}$ and $Soy_{i,t-1}$ denote the changes in the cattle herd and soybean planted area in $t-1$, respectively. The interaction terms $(Cattle_{i,t-1} \times SoyBr_{t-2})$ and $(Cattle_{i,t-1} \times SugarcaneBr_{t-2})$ capture the interaction between changes in the cattle herd in sample municipalities at $t-1$ and changes in the soybean and sugarcane planted areas, respectively, in Brazilian municipalities outside the sample at $t-2$. As controls, $Prices_{i,t-1}$ is a vector of cattle, soybean, and timber prices, while $Policies_{i,t}$ is a vector of public policies, including environmental fines, embargoed areas, protected areas, priority municipalities, the rural environmental registry (CAR), rural credit, and party diversity. Finally, $W_1 X_{j,t}$ denotes the vector of spatially lagged explanatory variables. Table 1 presents a description of all variables included in the empirical models.

Table 1. Description of variables used in the econometric model

Variable	Description
L1_Deforest	Annual deforestation rate (km^2) in municipality i at year $t-1$.
L1_Cattle	Number of cattle heads in municipality i at year $t-1$.
L1_Soybean	Soybean planted area (ha) in municipality i at year $t-1$.
L1_Cattle.L2_SoybeanBR	Interaction term capturing indirect effects of national soybean expansion at $t-2$ on cattle ranching in the Amazon at $t-1$.
L1_Cattle.L2_SugarBR	Interaction term capturing indirect effects of national sugarcane expansion at $t-2$ on cattle ranching in the Amazon at $t-1$.
L1_Wood_Price	Log of real timber prices (proxy for logging pressure).
L1_Soybean_Price	Weighted soybean price index based on exogenous price variation in Paraná.
L1_Cattle_Price	Weighted cattle price index based on exogenous price variation in Paraná.
Party_Composition	Diversity index of local political representation.
Rural_Credit	Log of total agricultural credit disbursed (R$).
Protected_Area	Share of municipal territory under protected areas.
Environmental_Fines	Value of environmental fines (R$) applied by IBAMA.
Priority_Mun.	Dummy variable for municipalities listed as priority for deforestation control.
Embargoes	Share of embargoed areas due to environmental infractions.
CAR	Share of municipal area registered in the Rural Environmental Registry (CAR).

Source: Prepared by the authors.

3.3 Dynamic Spatial Panel

The Dynamic Spatial Panel Model combines both spatial and temporal dependence in a single framework, which is particularly relevant for deforestation processes, where land-use dynamics in one municipality are often influenced by both past local deforestation and deforestation occurring in neighboring areas. The general specification follows Yu et al. (2008):

$$Y_{it} = \lambda W Y_{it} + \gamma Y_{i,t-1} + \rho W Y_{i,t-1} + X_{it}\beta + c_i + v_{it}, \tag{3}$$

where Y_{it} represents deforestation in municipality i at time t, W is a spatial weight matrix capturing geographic proximity between municipalities, X_{it} is a vector of explanatory variables (such as agricultural expansion, commodity prices, and conservation policies), c_i denotes unobserved fixed effects, and v_{it} is the idiosyncratic error term. The inclusion of both WY_{it} and $WY_{i,t-1}$ allows distinguishing instantaneous spatial interactions and dynamic spillovers over time. The parameters λ, γ, and ρ measure, respectively, the contemporaneous spatial dependence, temporal persistence, and lagged spatial effects.

To estimate the parameters, the model is fitted by Quasi-Maximum Likelihood (QML), which provides consistent results under weak distributional assumptions. The estimator is obtained by maximizing the following log-likelihood function:

$$\ln L(\theta) = T \ln |I - \lambda W| - \frac{1}{2\sigma^2} \sum_{t=1}^{T} v_t'(\theta) v_t(\theta), \tag{4}$$

where $\theta = (\lambda, \gamma, \rho, \beta, \sigma^2)$. Since the number of municipalities (n) is much larger than the number of years (T), a bias correction is applied to improve small-sample properties, resulting in the adjusted estimator:

$$\hat{\theta}^* = \hat{\theta} - \frac{\hat{B}}{T}. \tag{5}$$

This specification enables the identification of both direct effects—representing within-municipality impacts—and indirect or spillover effects transmitted through spatial dependence, offering a more comprehensive understanding of how agricultural expansion and conservation policies jointly shape deforestation dynamics across the Amazon region.

4. Results and Discussion

First, Table 2 presents the descriptive statistics of the variables used in the econometric estimations. The results show substantial heterogeneity across municipalities in the Legal Amazon, reflecting the region's diverse economic, environmental, and institutional conditions. Overall, these descriptive statistics illustrate the coexistence of consolidated agricultural frontiers and forest-dominated regions, reinforcing the need for spatial models capable of capturing both local and indirect effects of land-use dynamics on deforestation.

Table 2. Descriptive statistics

	Mean	Standard Deviation	Minimum	Maximum
	(1)	(2)	(3)	(4)
L1_Cattle	4,797.9290	2,4636.2800	-455,639.0000	441,738.0000
L1_Soybean	205.6926	2,308.6470	0.0000	63,908.7000
L1_Wood_Price	88.4818	85.5773	0.0000	959.9780
L1_Soybean_Price	205.6926	2,308.6470	0.0000	63,908.7000
L1_Cattle_Price	3,890.0880	1,1617.4600	0.0000	344,538.0000
Party_Composit	0.1117	0.2967	0.0000	1.0000
Rural_Credit	8,921,538.0000	22,500,000.0000	0.0000	320,000,000.0000
Protect_Area	0.2317	0.2951	0.0000	1.0000
Environ_Fine	3,137,128.0000	15,900,000.0000	0.0000	460,000,000.0000
Priority_Mun.	0.0335	0.1801	0.0000	1.0000
Embargoes	0.0178	0.2043	0.0000	10.7908
CAR	0.0240	0.0768	0.0000	0.7349

Source: Prepared by the authors.

The empirical strategy to select the best specification involves estimating a general model, the Dynamic Spatial Durbin Model (DSDM), and comparing it with other spatial models. The results are shown in Table 3. For the spatial models, we use a k-neighbor neighborhood criterion for the spatial weight matrices, with k ranging from 3 to 100 neighbors. Next, we compared the Dynamic Spatial Autoregressive Model (DSAR) with the DSDM by testing the joint non-significance hypothesis for the spatially lagged independent variables. The null hypothesis ($\beta_6 = 0$) was rejected by the χ^2 test, which yielded a value of 245.22 with 1% of statistical significance, indicating that the DSDM, which incorporates local externalities, is the better specification. Additionally, we tested the suitability of the dynamic model with a Likelihood-Ratio (LR) test, which resulted in a χ^2 value of 10.77, statistically significant at 1%, confirming that the phenomenon is indeed dynamic.

To test whether the SEM (Spatial Error Model) is more appropriate, we followed Elhorst's (2014) approach, testing if the parameters representing spatial spillovers of the independent variables are a multiplication of the indirect effects by the spatial interaction parameter: $\beta_6 = -\rho\beta_i$. We obtain a χ^2 test statistic of 219.54, significant at 1%, thus reinforcing the better performance of the SDSM. Next, a Hausman test confirmed that the fixed effects approach is adequate, with a χ^2 test statistic of 105.55, rejecting random effects.

To test the robustness of the estimates, we gradually introduced additional variables and compared the resulting coefficients with those from the benchmark specification (5). Across all models, the results consistently confirmed significant spatial dependence in deforestation (ρ), suggesting a dynamic decision-making process where land-use strategies are spatially interconnected. This finding aligns with previous evidence on spatial contagion and frontier dynamics in the Amazon (Igliori, 2006; Hargrave e Kis-Katos, 2013; Amin et al., 2019), as well as with the theoretical expectations of spatial econometric models (LeSage e Pace, 2009; Elhorst, 2014).

Given these strong spatial interactions, the coefficients reported in Table 3 should not be interpreted directly, but rather in terms of their direct, indirect, and total effects, as derived in Table 4. Direct effects capture intra-municipal changes in deforestation resulting from local land-use drivers, while indirect effects (or spatial spillovers) represent the propagation of these impacts across neighboring municipalities through economic and geographic linkages. The model's dynamic component also allows for a distinction between short-run and long-run effects, since deforestation processes display temporal persistence and delayed adjustment.

Table 4 reports these decomposed effects for the main land-use and institutional variables, both in the short and long term. As expected, long-run effects tend to be larger in magnitude, reflecting the cumulative nature of indirect land use change (ILUC) processes over time. Therefore, in the following discussion, we focus primarily on the total long-run effects (Total LR), which provide the most comprehensive measure of deforestation responses once spatial and temporal feedbacks are fully internalized.

Although cattle ranching is widely recognized as a dominant driver of Amazon deforestation (McManus et al. (2016)), its estimated marginal coefficient is not statistically significant in the baseline model. This outcome is likely explained by multicollinearity between local cattle expansion and its interaction with soybean expansion outside the region (Appendix A1), which inflates standard errors and masks the true underlying effect. When the total long-run effect is considered—combining direct, indirect, and displacement components—the results indicate that agricultural dynamics remain central to forest loss, operating both through local land conversion and through displacement effects driven by competition among expanding activities.[2]

When the total long-run effect is considered—combining direct, indirect, and displacement components—the results indicate that cattle dynamics remain the main contributor to forest loss. Despite the lack of statistical significance in the marginal coefficient, the overall magnitude of the long-run impact suggests that livestock expansion continues to play a central role in Amazon deforestation. Using within-sample variation in herd size, which grew by an average of two million heads per year during the study period, we estimate that cattle-related expansion could be associated with

[2]The methodological procedure used to calculate the implied deforested areas followed a consistent approach across variables. First, we derived the total long-run effect of each driver from the DSDM, combining direct, indirect, and interaction terms. This coefficient was then multiplied by the within-sample annual change of the corresponding variable, obtained from IBGE's agricultural and livestock surveys, and accumulated over the study period. The resulting predicted deforestation was compared to PRODES/INPE records to estimate the relative contribution of each driver to total forest loss.

Table 3. Dynamic Spatial Durbin Model (DSDM)

Variables	(1)	(2)	(3)	(4)	(5)
L1_Deforest	0.0830***	0.0804***	0.0776***	0.0656***	0.0481***
	(0.0207)	(0.0215)	(0.0207)	(0.0201)	(0.0192)
L1_Cattle	5.04E-07	5.04E-07	-8.89E-07	-9.09E-07	-1.41E-06***
	(4.86E-07)	(4.89E-07)	(6.53E-07)	(5.62E-07)	(5.33E-07)
L1_Soybean		2.88E-06***	2.86E-06***	2.99E-06***	3.04E-06***
		(9.05E-07)	(9.12E-07)	(8.64E-07)	(6.86E-07)
L1_Cattle.L2_SoybeanBR			1.61E-12**	1.67E-12**	2.67E-12***
			(8.13E-13)	(6.54E-13)	(6.34E-13)
L1_Cattle.L2_SugarBR			1.51E-12***	1.47E-12***	1.45E-12***
			(4.55E-13)	(3.90E-13)	(2.67E-13)
L1_Wood_Price				-4.32E-05	0.0001
				(0.0002)	(0.0002)
L1_Soybean_Price				3.00E-06	2.61E-06
				(3.74E-06)	(3.67E-06)
L1_Cattle_Price				4.06E-07	4.36E-07
				(1.01E-06)	(1.05E-06)
Party_Composition					0.0186
					(0.0326)
Rural_Credit					-2.05E-10
					(1.42E-09)
Protected_Area					-0.1159
					(0.1634)
Environmenta_Fines					-1.17E-09**
					(5.01E-10)
Priority_Mun.					-0.2158***
					(0.0436)
Embargoes					-0.0203
					(0.0254)
CAR					-0.7174**
					(0.3317)
WL1_Cattle	1.64E-06***	1.65E-06***	1.21E-06***	1.19E-06***	1.54E-06***
	(4.38E-07)	(4.55E-07)	(3.93E-07)	(3.15E-07)	(4.88E-07)
WL1_Soybean		3.05E-06	3.11E-06	3.76E-06	4.28E-06***
		(2.69E-06)	(2.70E-06)	(2.29E-06)	(1.32E-06)
WL1_Wood_Price				-0.0010***	-0.0007***
				(0.0004)	(0.0003)
WL1_Wood_Price				-1.62E-05***	-1.70E-05***
				(5.00E-06)	(5.75E-06)
WL1_Cattle_Price				1.12E-06	1.21E-06
				(8.39E-07)	(1.05E-06)
W_Party_Composition					0.0165
					(0.0534)
W_Rural_Credit					1.27E-09*
					(7.11E-10)
W_Protected_Area					-0.5356
					(0.4571)
W_Environmental_Fines					4.42E-10
					(4.77E-10)
W_Priority_Mun.					-0.0669
					(0.0847)
W_Embargoes					-0.0138
					(0.0471)
W_CAR					0.2783
					(0.2349)
Spatial_rho (ρ)	0.7602***	0.7574***	0.7543***	0.7428***	0.7292***
	(0.0163)	(0.0162)	(0.0162)	(0.0135)	(0.0119)
Observations	4428	4428	4428	4428	4428
AIC	8125.33	8119.68	8102.34	8061.98	7993.97
BIC	8170.10	8170.85	8153.51	8113.14	8045.14
DSDM x DSAR: $\beta_6 = 0$					
X^2 statistic	13.99	16.70	10.06	76.86	245.22
p-value	0.0002	0.0002	0.0065	0.0000	0.0000
DSDM x SEM: $\beta_6 = -\rho\beta_i$					
X^2 statistic	10.03	28.09	3.10	62.26	219.54
p-value	0.0015	0.0000	0.2127	0.0000	0.0000

Source: Prepared by the authors. *Note*: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4. Direct, indirect, and total effects (short- and long-run).

	Short-run effects			Long-run effects		
Variable	Direct	Indirect	Total	Direct	Indirect	Total
L1_Cattle	-1.32E-06	1.58E-06	2.59E-07	-1.38E-06	1.70E-06	3.14E-07
	(1.22E-06)	(2.97E-06)	(3.98E-06)	(1.32E-06)	(3.73E-06)	(4.84E-06)
L1_Soybean	4.77E-06**	2.20E-05**	2.67E-05**	5.32E-06**	2.72E-05**	3.25E-05**
	(2.20E-06)	(1.12E-05)	(1.26E-05)	(2.42E-06)	(1.37E-05)	(1.54E-05)
L1_Cattle.L2_SoybeanBR	3.35E-12*	6.99E-12*	1.03E-11*	3.64E-12*	8.95E-12*	1.26E-11*
	(2.03E-12)	(4.24E-12)	(6.26E-12)	(2.20E-12)	(5.43E-12)	(7.63E-12)
L1_Cattle.L2_SugarBR	1.78E-12***	3.71E-12***	5.49E-12***	1.93E-12***	4.75E-12***	6.68E-12***
	(5.48E-13)	(1.15E-12)	(1.70E-12)	(5.96E-13)	(1.48E-12)	(2.07E-12)
L1_Wood_Price	-0.0001	-0.0023***	-0.0024***	-0.0002	-0.0028***	-0.0029***
	(0.0002)	(0.0008)	(0.0009)	(0.0002)	(0.0010)	(0.0011)
L1_Soybean_Price	-1.33E-06	-0.0001*	-0.0001	-2.01E-06	-0.0001*	-0.0001
	(5.14E-06)	(2.84E-05)	(3.22E-05)	(5.71E-06)	(3.49E-05)	(3.93E-05)
L1_Cattle_Price	8.48E-07	5.01E-06	5.86E-06	9.60E-07	6.18E-06	7.14E-06
	(1.22E-06)	(6.28E-06)	(7.15E-06)	(1.34E-06)	(7.70E-06)	(8.70E-06)
Party_Composition	0.0256	0.0905	0.1161	0.0283	0.1132	0.1415
	(0.0564)	(0.3155)	(0.3561)	(0.0625)	(0.3869)	(0.4342)
Rural_Credit	2.00E-10	3.76E-09	3.96E-09	2.56E-10	4.57E-09	4.82E-09
	(1.74E-09)	(7.65E-09)	(8.55E-09)	(1.89E-09)	(9.36E-09)	(1.04E-08)
Protected_Area	-0.2991*	-2.1300**	-2.4292**	-0.3430*	-2.6156**	-2.9586**
	(0.1762)	(0.9394)	(1.0049)	(0.1908)	(1.1444)	(1.2267)
Environmental_Fines	-1.24E-09	-1.31E-09	-2.55E-09	-1.33E-09	-1.76E-09	-3.10E-09
	(7.84E-10)	(4.60E-09)	(5.11E-09)	(8.67E-10)	(5.62E-09)	(6.22E-09)
Priority_Mun.	-0.2818***	-0.7609*	-1.0427**	-0.3085***	-0.9614**	-1.2699**
	(0.0739)	(0.3916)	(0.4308)	(0.0808)	(0.4780)	(0.5249)
Embargoes	-0.0276	-0.0944	-0.1220	-0.0304	-0.1182	-0.1486
	(0.0539)	(0.2473)	(0.2872)	(0.0594)	(0.3042)	(0.3499)
CAR	-0.7540***	-0.8451	-1.5990***	-0.8114***	-1.1361	-1.9475***
	(0.2856)	(0.6240)	(0.6050)	(0.3015)	(0.7406)	(0.7367)

Source: Prepared by the authors. *Note*: *** Significant at 1%; ** 5%; * 10%. Robust Standard Errors. Direct, indirect, and total effects computed from partial derivatives of the DSDM following LeSage e Pace (2009). Short-run effects represent contemporaneous impacts; long-run effects incorporate dynamic feedbacks over time.

approximately 70,000 km² of deforestation between 2003 and 2011, corresponding to nearly 46% of total observed forest loss. This highlights that the influence of cattle ranching operates not only through local land conversion but also via displacement effects driven by competition with other expanding agricultural activities.

In contrast, soybean expansion presents a positive and statistically significant direct effect on deforestation at the 1% level. Based on the observed within-sample variation, with an average annual increase of approximately 270,000 hectares in the sampled municipalities, the direct impact of soybean expansion accounts for around 2,400 km² of forest clearing during the period, equivalent to 1.5% of total deforestation. However, when displacement effects are considered—capturing how soybean expansion in other regions pushes cattle ranching into forested areas—the overall impact becomes substantially larger. The external expansion of soybean in non-Amazon regions indirectly contributed to approximately 19,000 km² of additional deforestation in the Amazon, or 12.2% of total forest loss. Combining both local and external effects, soybean expansion as a whole is associated with 21,400 km² of forest suppression, equivalent to 13.7% of total deforestation between 2003 and 2011. These results reinforce the interpretation that soybean expansion contributes to Amazon deforestation primarily through indirect land-use displacement, rather than direct cropland conversion.

Although commercial-scale sugarcane cultivation is prohibited within the Amazon biome, we find a statistically significant and substantial indirect impact of sugarcane expansion in other Brazilian regions on Amazon deforestation. These indirect effects correspond to about 42,300 km² of forest suppression, or 26.7% of the total deforestation observed between 2003 and 2011. This result is consistent with empirical evidence showing that biofuel-driven expansion can induce cross-regional leakage effects (Lapola et al. (2010); Andrade de Sá et al. (2013); Jusys (2016); SantAnna (2024)), reinforcing the link between energy policy and land-use change in tropical frontiers.

Additionally, considering market conditions and conservation policies, we found statistically significant coefficients for wood prices, the expansion of protected areas, priority municipalities, and the Rural Environmental Registry (CAR). Higher values for forest goods, such as timber, are positively associated with forest conservation, consistent with previous findings. Likewise, conservation policies—including the expansion of protected areas, the CAR, and the designation of Priority Municipalities—are linked to lower deforestation rates. However, the potential endogeneity of these variables to deforestation dynamics complicates causal interpretation, even when spatial and temporal dependencies are taken into account.

From a regional perspective, the spatially explicit results reveal that agricultural expansion and conservation policies interact heterogeneously across the Amazon. Indirect effects, particularly those arising from soy and sugarcane expansion outside the biome, highlight how distant production shocks propagate through land markets, leading to forest loss in agricultural frontier zones. These spatial spillovers underscore that deforestation in the Amazon cannot be fully understood in isolation from broader national and global dynamics. Effective mitigation therefore requires coordinated cross-regional strategies that align agricultural production, market incentives, and conservation enforcement to address deforestation as an integrated spatial process rather than a localized phenomenon.

5. Final Remarks

Rising global demand for food and biofuels has intensified agricultural expansion, often at the expense of tropical forests. A key question in the literature is whether it is possible to meet this growing demand while preserving forest ecosystems, particularly in the Brazilian Amazon. While cattle ranching remains the dominant direct driver of deforestation, recent evidence points to substantial indirect effects from land-use changes triggered by soy and sugarcane expansion in other regions. These spatial and temporal spillovers complicate empirical estimations, keeping the scale of indirect land-use change (ILUC) effects an open challenge.

This study examines economic, political, and land-use dynamics between 2002 and 2011 using a spatial dynamic panel model to quantify the indirect impacts of soy and sugarcane expansion on Amazon deforestation. The results indicate that soy expansion accounted for approximately 21,400 km² of forest loss (13.7% of the total), with nearly 90% arising from indirect displacement effects. Although sugarcane cultivation is prohibited within the Amazon, its expansion elsewhere indirectly contributed to an estimated 42,300 km² of deforestation (26.7% of the total).

Overall, the findings reveal that the expansion of high-value crops, while supporting global commodity and energy markets, induces significant indirect environmental costs. Policies such as the Soy Moratorium and biofuel incentives partially mitigate direct pressures but fall short of addressing cross-regional displacement mechanisms. Because agricultural productivity tends to be lower in frontier areas, displaced activities demand more land, amplifying forest loss. Effective mitigation thus requires integrated policies that internalize spatial feedbacks and account for indirect land-use dynamics within broader development strategies.

However, this study has limitations that open avenues for further research. Future work should extend the analysis to other crops with increasing spatial relevance, such as maize and oil palm, and incorporate more recent data to assess the renewed surge in deforestation after 2012. Moreover, adopting a multiscale perspective could better capture regional heterogeneities in displacement and land-use dynamics. Even so, this research advances the spatial understanding of Brazil's agricultural frontiers by showing how regional crop expansions in the South, Southeast, and parts of the Center-West and Northeast can indirectly induce deforestation in areas of the Brazilian Amazon.

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A.1. Correlation

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
X1 Party_Composit	1													
X2 L1_Wood_Price	0.0371	1												
X3 L1_Soybean_Price	0.0178	-0.0096	1											
X4 L1_Cattle_Price	-0.0126	-0.1483	0.0554	1										
X5 L1_Cattle	-0.0046	0.0675	-0.0136	-0.0416	1									
X6 L1CattlL2Soyb	-0.0049	0.0401	-0.0066	-0.0214	0.8077	1								
X7 L1CattlL2Sugar	-0.0181	0.0995	-0.0138	-0.0441	0.4493	0.0095	1							
X8 L1_Soybean	-0.0114	0.0344	-0.0109	-0.0264	0.0073	0.0027	-0.0005	1						
X9 Rural_Credit	-0.0200	0.1038	-0.0233	-0.0842	0.0328	0.0267	0.0449	0.3339	1					
X10 Protect_Area	0.0287	-0.0660	-0.0380	-0.0844	-0.0032	0.0206	-0.0340	-0.0394	-0.1355	1				
X11 Environ_Fine	0.0164	0.1191	-0.0152	-0.0539	0.0404	0.0586	0.0887	0.0222	0.1042	0.0168	1			
X12 Priority_Mun.	0.0009	0.2449	-0.0153	-0.0552	0.1220	0.1671	0.0355	0.0839	0.1192	0.0033	0.3163	1		
X13 Embargoes	-0.0153	0.0324	-0.0049	-0.0173	-0.0228	-0.0114	0.0014	-0.0241	0.0279	0.0025	0.1176	0.0441	1	
X14 CAR	0.0242	0.2639	-0.0192	-0.0479	0.0232	0.0428	-0.0138	0.0806	0.3097	-0.1274	0.1294	0.3028	0.0396	1

Source: Prepared by the authors.